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Technical note

Automatic calibration of a distributed catchment model

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Abstract

Parameters of hydrologic models often are not exactly known and therefore have to be determined by calibration. A manual calibration depends on the subjective assessment of the modeler and can be very time-consuming though. Methods of automatic calibration can improve these shortcomings. Yet, the high number of parameters in distributed models makes special demands on the optimization. In this paper a strategy of imposing constraints on the parameters to limit the number of independently calibrated values is outlined. Subsequently, an automatic calibration of the version SWAT-G of the model SWAT (Soil and Water Assessment Tool) with a stochastic global optimization algorithm, the Shuffled Complex Evolution algorithm, is presented for a mesoscale catchment.

Keywords: Distributed models; Calibration; Parameter estimation; SWAT; SCE-UA

1. Introduction

A complex hydrologic model is generally characterized by a multitude of parameters. Due to spatial variability, measurement error, etc., the values of many of these parameters will not be exactly known. Therefore, in most cases a model calibration will be necessary.

The success of a manual calibration essentially depends on the experience of the modeler and their knowledge of the basic approaches and interactions in the model. A manual calibration therefore always is subjective to some extent. Moreover, it can be extremely time consuming.

Methods of automatic calibration can improve these shortcomings. Following, results from an automatic calibration of a modified version of the watershed model SWAT (Soil and Water Assessment Tool, Arnold et al., 1998) with a stochastic global optimization algorithm, the Shuffled Complex Evolution (SCE) algorithm developed by Duan et al. (1992), are presented. The SCE algorithm has been applied to different physically based hydrologic models (Duan et al., 1992; Sorooshian et al., 1993; Luce and Cundy, 1994; Gan and Biftu, 1996; Kuczera, 1997) and proved to be an efficient instrument for the automatic optimization.

SWAT is an example for distributed models relying on a physically based description of the runoff generation and the effects of different land covers. Models of this type are needed for the assessment of effects of land use changes on the water cycle and the transport of water constituents. Compared to the models used in the above mentioned studies, a special feature of distributed models is the greater number of parameters which

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potentially need to be calibrated. A catchment modeled with SWAT will be subdivided into spatial subunits (subbasins and hydrotopes or hydrologic response units, respectively) which are explicitly parametrized with respect to the land cover, the soil, etc.. Thus, the number of parameter values characterizing the catchment will be very high.Though many inputs into SWAT are based on readily available information, some uncertainty in these inputs is inevitable. Therefore, in most SWAT modeling studies, inputs are allowed to vary within a realistic uncertainty range to calibrate output to monthly or annual values (Arnold and Allen, 1996).

2. The hydrologic model

The hydrologic model used in this study is a modified version of the Soil and Water Assessment Tool (SWAT; Arnold et al., 1998). SWAT was developed to predict the impact of land management practices on water, sediment and agricultural chemical yields in large complex watersheds with varying soils, land use and management conditions over long periods of time. To satisfy this objective, the model (a) is physically based, (b) uses readily available inputs, (c) is computationally efficient, and (d) is continuous time operating on a daily time step. Major model components include: weather, hydrology, soil temperature, plant growth, nutrients, pesticides, and land management. In the present study only hydrologic processes are considered.

In each of the spatial subunits of a watershed model, the water balance is represented by four storage volumes: snow, soil profile, shallow aquifer, and deep aquifer (Fig. 1). The soil profile can be subdivided into multiple layers. Soil water processes include infiltration, evaporation, plant uptake, lateral flow, and percolation to lower layers. Percolation from the bottom of the soil profile recharges the shallow aquifer. A recession constant is used to lag flow from the aquifer to the stream. Other shallow aquifer components include evaporation, pumping withdrawals, and seepage to the deep aquifer.

The hydrologic components of the model have been validated for numerous watersheds (Arnold and Allen, 1996) and a comprehensive validation of streamflow was performed for the entire conterminous U.S. (Arnold et al., 1999). The application of SWAT to a low mountain range catchment in central Germany (see below) required some changes in the model though. The considered catchment is characterized by steep slopes and shallow soils over hard rock aquifers. Therefore, the contribution of groundwater (baseflow) to the streamflow is relatively small, whereas much near-surface lateral flow (interflow) is produced. To take account of this special situation the calculation of the percolation and the interflow had to be revised. The new model version was named SWAT-G (Eckhardt et al., 2001).

3. The optimization algorithm

The SCE algorithm (Duan et al., 1992) belongs to the family of genetic algorithms. In its first step a sample of points is distributed stochastically over the feasible part of the parameter space which is confined by the lower and upper bounds of the parameter values. Every point is thought to represent a member of a population of living beings. Each individual is characterized by its genetic information, a complete set of parameter values. By changing the genetic information—the parameter values—the population develops towards an optimum of fitness, that is an optimum of the objective function desribing the correspondence between a model output variable and measured values. To this purpose the initial sample is partitioned into several sub-samples, so-called complexes. In every complex varying combinations of points produce offspring using the downhill simplex procedure of Nelder and Mead (1965). The probability of an individual to take part in the reproduction is proportional to its fitness. 'Old' points of lower fitness are replaced by the offspring. The proceeding towards a global optimum is supported by (a) the possibility that new points are spontaneously created in the feasible parameter space ('mutation') and (b) a regular recombination of the points into new complexes ('shuffling').

The algorithm was programmed by Qingyun Duan at the Department of Hydrology & Water Resources of the University of Arizona who kindly made its source code available.

Because a catchment modeled with SWAT will be

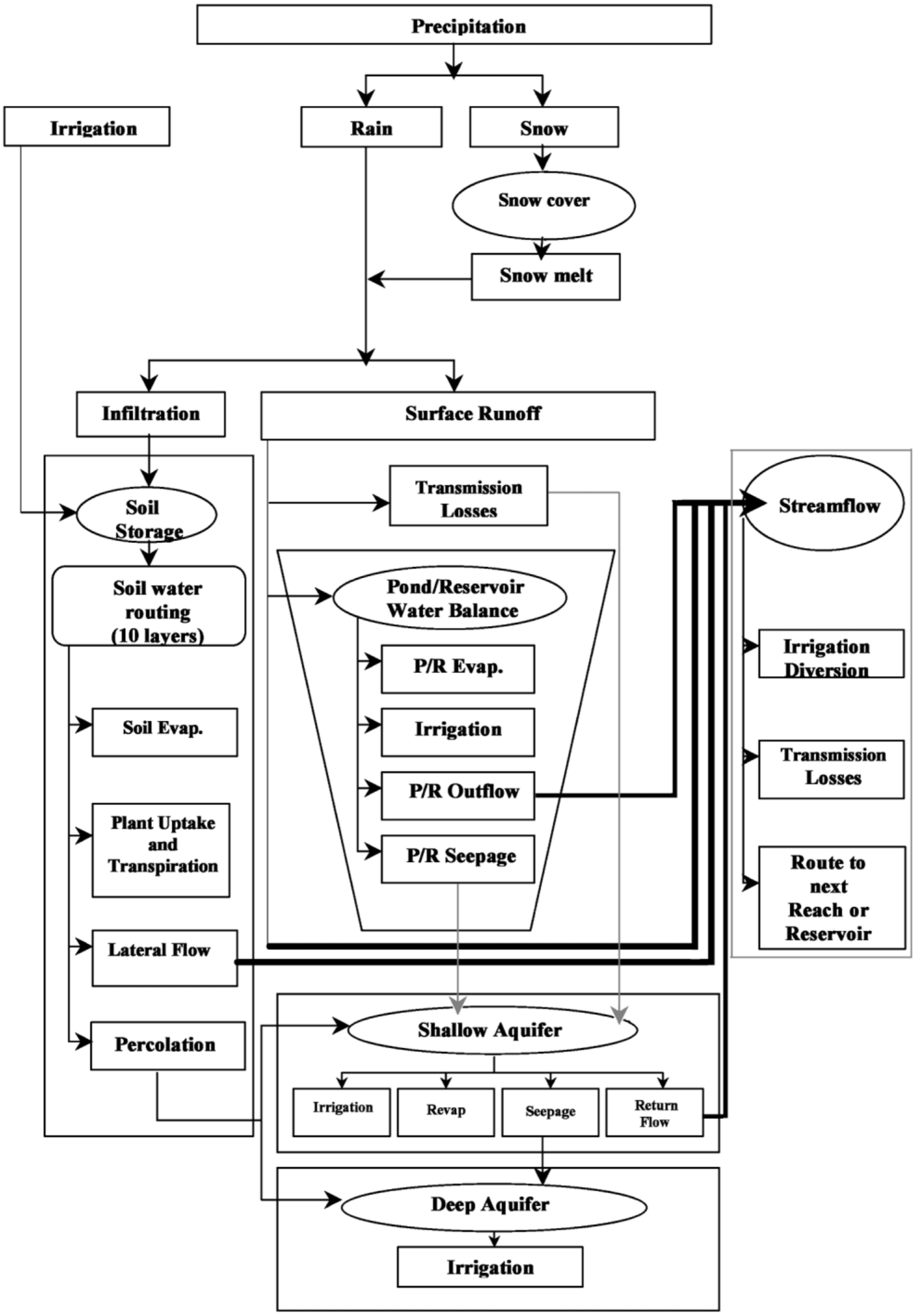

Fig. 1. Schematic of pathways available for water.

subdivided into spatial subunits (subbasins, hydrotopes, HRUs) which are explicitly parametrized, the number of parameter values characterizing the catchment will be very high. It is neither possible nor meaningful to independently optimize all these parameter values. Therefore, the programs for the automatic calibration have been complemented by an additional module enabling the user to formulate constraints and interdependencies of the model parameters. It is thereby possible

1. to optimize only a few selected parameter values while others simultaneously are adjusted in previously defined ratios
2. to guarantee that the magnitude relation (if it is known) of two parameters respectively which are varied in overlapping intervals is preserved during the optimization.

With the first of these two options a spatial pattern of a parameter (hydraulic conductivity of the soil for instance) can be defined which during the calibration is no more spatially differentiated but only modified as a whole. The number of free parameters which need to be adjusted thus can be considerably reduced.

The application and the benefits of these features are demonstrated below.

4. The catchment

A model for the Dietzhölze catchment in central Germany has been etablished. The Dietzhölze is a small river in a low mountain range in the federal state of Hesse. The area of its catchment amounts to 81 km^2. The elevation ranges from 250 to 685 m above sea level, the average hillslope is 20%. Based on a digital elevation model the catchment was subdivided into five subbasins (Fig. 2).

By superimposing the information on land cover and soils altogether 35 hydrotopes or HRUs respectively were formed which represent the smallest spatial units assumed to be homogeneous in their hydrologic behavior.

Land use information was derived from Landsat TM5 satellite images (Nöhles, 2000). Five different land use categories are distinguished: coniferous wood (40% of the area), deciduous wood (21%), pasture (17%), range and farm land (13%), and settlement (9%). The soil is dominated by shallow cambisols over schist and greywacke (HLUG, 2000).

Fig. 2. Digital elevation model and subbasin boundaries for the Dietzhölze catchment.

5. Results and discussion of the automatic calibration

The model was calibrated against 3 hydrologic years (1991–1993) of daily measured runoff at the catchment outlet. A previous sensitivity analysis showed which parameters should be given priority in the optimization. Concerning land use and soils these are the curve number (USDA-SCS, 1972), the maximum potential interception, the maximum leaf area index, the thickness of the hard rock layer representing the schist and greywacke underneath the shallow cambisols, the density, the available water capacity and the saturated conductivity of the soil. Furthermore, parameters determining the delay of the surface runoff, the groundwater recharge and the baseflow recession were optimized.

To consider only sensitive parameters is a first step to reducing the number of calibration parameters and thus to keeping the runtime of the optimization in reasonable bounds. A second step is to optimize these parameters only for a few selected crops and soils or soil layers respectively. The corresponding values for other crops and soils or soil layers then can be linked to these calibration parameters in previously defined ratios as mentioned above.

As an example consider the saturated hydraulic

Table 1
Explicitly calibrated model parameters

Parameter	Lower bound	Upper bound	Optimized value
Snow melt rate (mm/d/°C)	1.00	3.00	1.06
Surface runoff lag time (d)	0.10	1.00	0.35
Curve number for coniferous wood	50.0	60.0	59.9
Maximum potential interception for coniferous wood (mm)	3.00	6.00	4.29
Manning's 'n' value for overland flow ($m^{-1/3}$ s)	0.20	0.50	0.38
Groundwater recession coefficient (d^{-1})	0.030	0.060	0.056
Delay of the groundwater recharge (d)	1.0	20.0	1.0
Deep aquifer percolation fraction	0.00	0.80	0.52
Thickness of the rocky base of soil no.202[a] (mm)	1000	5000	1920
Thickness of the rocky base of soil no.2458[b] (mm)	3000	10000	6630
Density, soil no. 2458[b], third layer (g/cm^3)	1.50	1.60	1.50
Density of the bedrock (g/cm^3)	2.51	2.64	2.64
Available water capacity, soil no.2458[b], first layer (mm/mm)	0.16	0.20	0.16
Saturated conductivity, soil no.202[a], third layer (mm/h)	1.0	45.0	44.8
Saturated conductivity, soil no.2458[b], third layer (mm/h)	10.0	85.0	85.0
Anisotropy factor[c], soil no.2458[b], third layer	2.00	8.00	7.96
Maximum leaf area index for coniferous wood	4.0	14.0	8.4
Maximum leaf area index for pasture	1.5	5.5	1.8

[a] Shallow cambisol on the lower slope.
[b] Shallow cambisol on the upper slope.
[c] Only available in the SWAT version SWAT-G (Eckhardt et al., 2001).

conductivity. The model contains 10 different soils. Forty-four conductivity values are assigned to the layers of these soils, too many to calibrate them individually. Therefore, the calibration of the hydraulic conductivity was confined to one layer respectively of two soils representing the shallow cambisols on the upper and the lower slope. Together, they cover more than 66% of the catchment area. All other values of the saturated conductivity were adjusted in fixed ratios to these calibration parameter values. The ratios were derived from empirical rules considering the soil type and its bulk density (KA3, 1982).

In this way, 18 parameter values remained to be optimized explicitly while 143 others were simultaneously adjusted in fixed ratios. Table 1 shows the explicitly calibrated model parameters, their upper and lower bounds of variation and the optimization results. The ranges were choosen from tables found in literature (e.g. McCuen, 1998, for roughness coefficients and curve numbers). Furthermore, their definition was influenced by experiences made in a manual calibration of a similar catchment in the same region.

Using the mean square error as objective function, nearly 18,000 model runs had to be executed automatically until the optimization was terminated because no further amelioration could be obtained. Some of the optimized parameters equal the defined upper or lower bounds. It seems to be a problem to simulate the quick catchment response to precipitation. The optimized values of the curve number, the density of the soil, its available water capacity, hydraulic conductivity and anisotropy all favor a high contribution of direct runoff (surface runoff and interflow) to the streamflow.

The focus on the direct runoff is supported by the choice of the objective function. Using the mean square error the minimization of large differences between the modeled and the observed runoff gains a disproportionately high priority to the minimization of small differences. Yet, the largest differences are found underneath streamflow peaks where the fast runoff components dominate. Further, the high value of the curve number could reflect that the soils were not correctly attributed to the SCS soil groups. To define the curve number range it was assumed that the soils belong to the hydrologic soil group B. Perhaps soil group C would have been a more

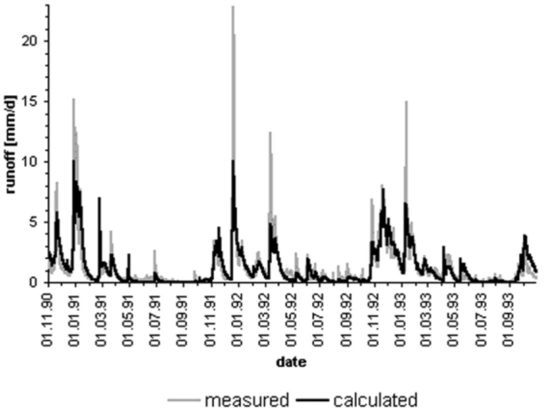

Fig. 3. Measured and calculated daily streamflow after the automatic model calibration.

appropriate choice. To admit a higher curve number in turn would have reduced the need for extreme values of the other parameters. Last but not least, difficulties to simulate the fast hydrologic catchment response will partially be caused by the relatively coarse spatial resolution of the model. Thereby, higher importance is attached to those land covers and soils already dominating the base data. In case of the Dietzhölze catchment these are forest and soils on the upper slope and hilltops, the land cover and the soils with the slowest hydrologic response.

In Figs. 3 and 4, the daily and monthly streamflow calculated by the automatically calibrated model is compared to the observed runoff. Mean values of

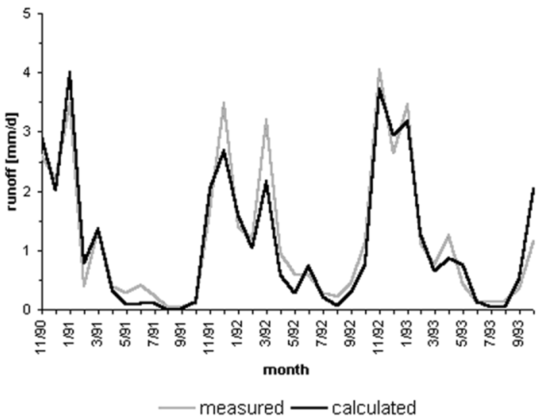

Fig. 4. Measured and calculated monthly streamflow after the automatic model calibration.

Table 2
Results of the calibration based on the daily streamflow

	Observed	Calculated
Mean annual streamflow (mm/d)	1.18	1.13
Standard deviation (mm/d)	1.94	1.51
Mean winter streamflow (mm/d)	2.00	1.91
Mean summer streamflow (mm/d)	0.38	0.36
Model efficiency[a]		0.70
Correlation		0.84

[a] Nash and Sutcliffe (1970).

the streamflow, the model efficiency (Nash and Sutcliffe, 1970) and the correlation of the measured and the calculated streamflow are listed in Table 2.

The mean annual runoff is slightly underestimated by 4%. A model efficiency (Nash and Sutcliffe, 1970) of 0.70 and a correlation of 0.84 are obtained for the daily values though. The model efficiency for the 36 monthly means of the considered period amounts to 0.91. A model validation using the daily streamflow in the 3 following hydrologic years (1994–1996) confirms the calibration result (efficiency: 0.73, correlation: 0.86).

6. Conclusions

First it has to be assessed how good the obtained model efficiencies are. Efficiencies of different catchment models are not directly comparable because they are influenced by the variability of the respective measurements (the efficiency being 1 minus the variance of the residuals divided by the variance of the measured values). Results of previously published investigations can give an impression of the approximate level the efficiency should reach though.

Krysanova et al. (1998) presented a model partially derived from SWAT called SWIM. Testing it for five mesoscale watersheds in Germany over 3- to 5-year periods of daily runoff values they obtained model efficiencies ranging from 0.68 to 0.85. Using SWAT, King and Arnold (1998) calibrated a model of a mesoscale watershed in Mississippi over one year of daily streamflow. The resulting efficiency was 0.78. So it seems that an acceptable calibration level has been reached by means of the automatic opimization comparable to that of similar studies and probably not far from its potential optimum.

Finally, the expenditure of work has to be assessed. A manual calibration is more or less a process of trial and error. In general, parameter values have to be changed and the model has to be rerun many times by the user. On the other hand, the automatic calibration only requires two input files to be filled out once. These files contain the information controling the program, the measured values the model output is to compare with and the declarations of parameter constraints and interdependencies. In our example, on an IBM RS/6000 workstation, the optimization procedure took about 6 days. So some patience is required for certain but the modeler is free for other work in the meantime.

The results presented in this study show that also distributed hydrologic models as complex as SWAT can successfully be automatically calibrated.

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